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Development of Watershed and Reference Loads for a TMDL in Charleston Harbor System, SC.

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ABSTRACT

It is essential to determine point and non-point source loads and their distribution for development of a dissolved oxygen (DO) Total Maximum Daily Load (TMDL). A series of models were developed to assess sources of oxygen-demand loadings in Charleston Harbor, South Carolina. These oxygen-demand loadings included nutrients and BOD. Stream flow and nutrient concentration data from watersheds draining to the Charleston Harbor System were used to establish land use specific watershed loadings to assess existing watershed conditions. Nutrient and DO data collected from 15 stations were grouped into two categories: dry weather and wet weather. Then, the data were evaluated with respect to different types of land use. It was found that nutrient concentrations and DO correlated with percentage of urban land use and percentage of forest reasonable well.

KEYWORDS. Non-point source, nutrient loading estimation, multiple regression.

INTRODUCTION

Charleston Harbor System (CHS) is located on the coast of South Carolina. The CHS consists of the Charleston Harbor and three major contributing rivers: the Ashley, Cooper and, Wando Rivers. The CHS drains over 1,200 square miles directly, with a larger area contributing freshwater flow to Lake Moultrie, which flows from Pinopolis Dam to the West Cooper River. Figure 1 shows general setting of the project study area.
The Cooper and Ashley Rivers have both been identified as impaired for dissolved oxygen (DO) under Section 303(d) of the Clean Water Act (US EPA, 1972). Modeling efforts were made throughout the 1990s to identify the sources and conditions influencing dissolved oxygen in the CHS and to develop a Total Maximum Daily Load (TMDL) for the DO.

Watershed non-point source impact on the dissolved oxygen (DO) of an impaired stream is crucial in the effort to develop the TMDLs. Typically, two different approaches are utilized in practice to estimate non-point source loading. One approach is to use existing watershed models, such as HSPF, to simulate non-point source loading. A series of nitrogen loading models, based on the complexity of processes being simulated, have recently been developed for poorly drained coastal watersheds (Skaggs et al., 2003; Amatya et al., 2003) Another approach is to develop a methodology to estimate non-point source loading based on the existing stream flow and water quality sample data and other information, such as soils, land cover and land use (Amatya et al., 2004).

In the watershed modeling approach, calibration is a necessary step before the model can be used for validation and prediction. Therefore, a reasonable amount of sample data, to which the model is calibrated, is often required. For the ongoing CHS project, very limited non-point source sample data free of tidal influence were collected in a relatively small area. Thus, the watershed modeling approach was not chosen to simulate non-point source loading, but was used to predict stream flow only.

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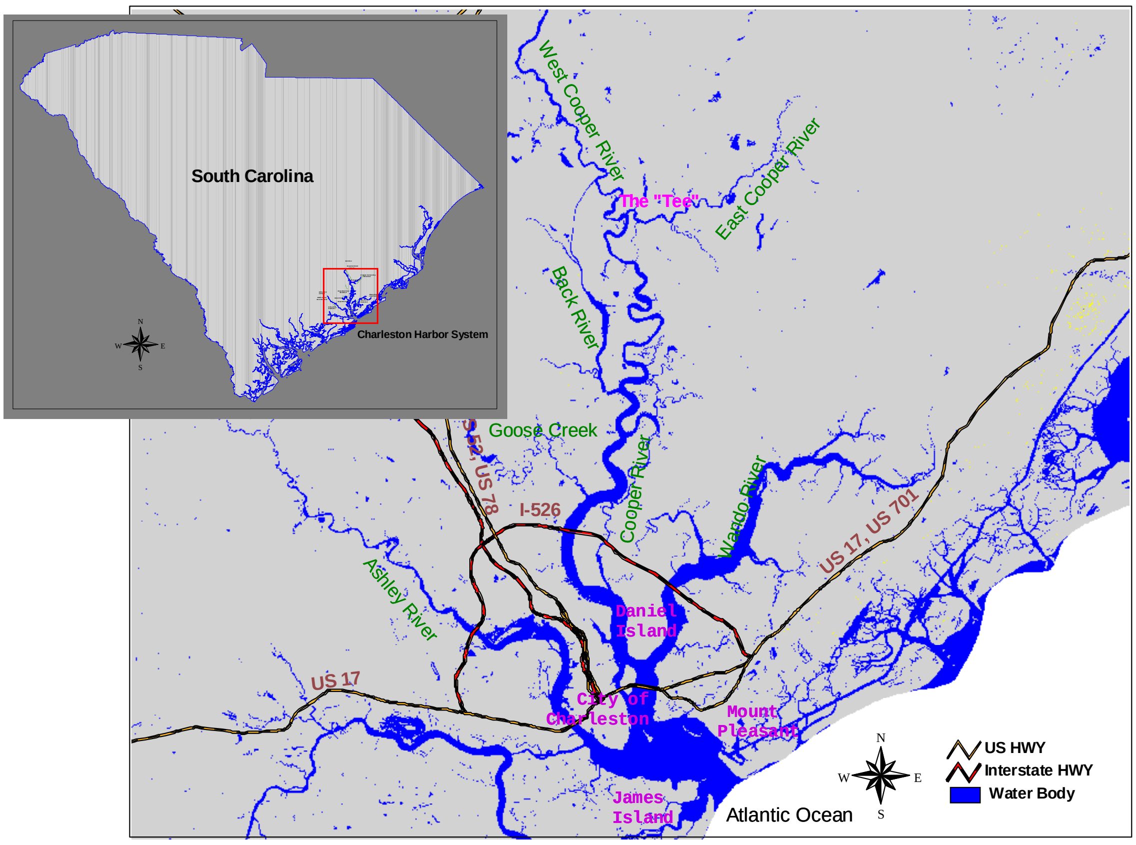


Figure 1. General Setting of the Project Study Area

WATERSHED

The 1,200 square miles CHS watershed was delineated into a series of sub-watersheds in order to estimates stream flows with the watershed model. The sub-watersheds were delineated to represent the appropriate hydrologic connectivity shown in Figure 2. The National Elevation Dataset (NED), National Hydrography Dataset (NHD), and 1992 USGS Multi-Resolution Land Coverage (MRLC) datasets were used in delineation.

The MRLC was used to determine prominent land use activities in each sub-watershed. This coverage was selected as the best available source of activities in the basin at the time of model development. In general, in the upper Ashley, upper Cooper and upper Wando watersheds, forest and pasture are dominant while in the lower part of the watershed urban development and residential land use are dominant.

From late 1970's to present, various non-point source sample data were collected at various locations throughout the watershed by different agencies. Figure 3 presents the non-point source sample locations in the watershed, where the sample data were relatively complete and were available to us for the study. For example, stream flow and nutrient concentrations data at the sampling location JJG-NPS-4 served the purpose for obtaining reference loads from a 200 ha first order, forested watershed within the Santee Experimental Forest (Binkley, 2001). The watershed is located at the headwaters of Huger Creek, a tributary of East Cooper River.

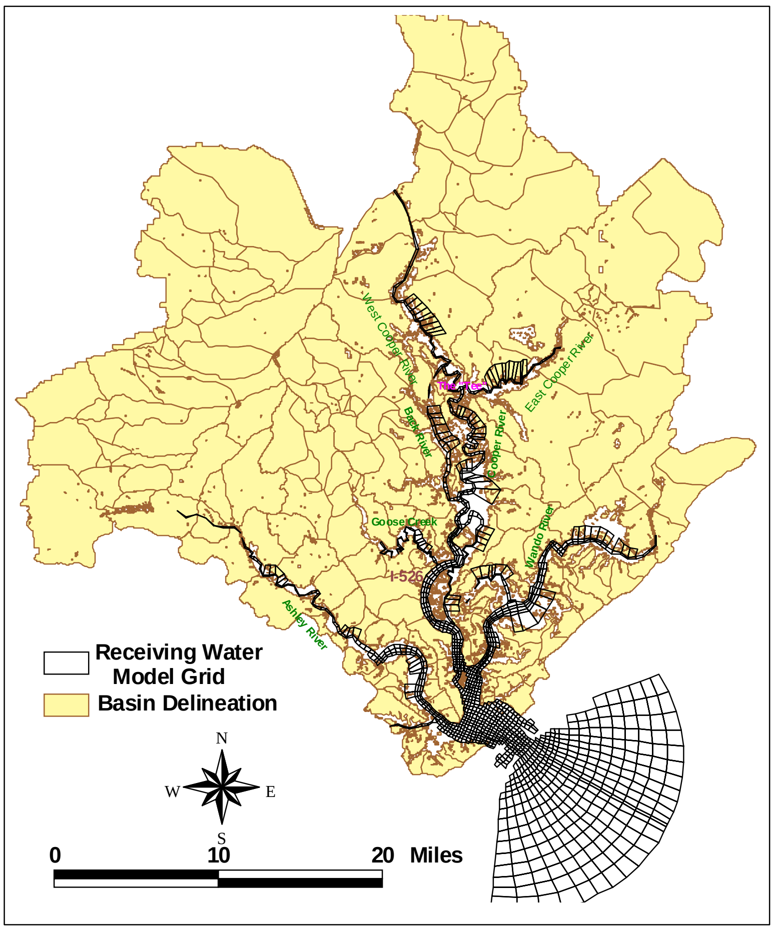


Figure 2. Charleston Harbor System Watershed Delineations

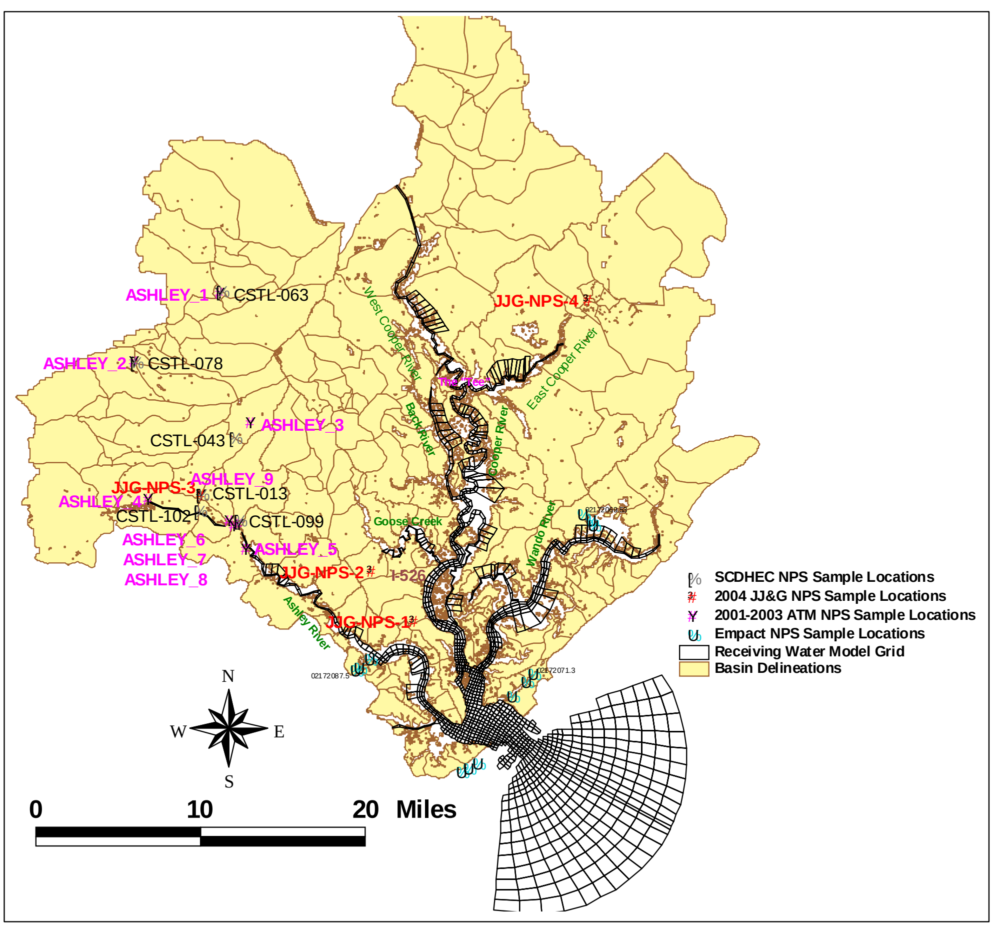


Figure 3. Non-Point Source Sample Locations

METHOD

To develop non-point source loadings from a watershed with complex land uses is generally a challenging task. Export coefficients are often used to generate seasonal or annual nutrient loadings from a field with a given land management practice (Amatya et al., 2003). Export Coefficient is defined as annual nutrient loading at the field edge (kg/ha/yr) and is frequently used by regulators and planners for assessing cumulative nutrient loadings from watersheds into receiving waters. Loading rates for each individual stream reach are directly extrapolated from the literature values based on soil and land management practice on the parcel of land drained by that reach. However, effects of rainfall on drainage outflow are rarely considered. Similarly, export coefficients do not reflect the effects of change in land use and management practices on both the stream outflows and nutrient concentrations. However, these values continue to be built up in the literature for lands with different management practices (Frink, 1991; Beaulac and Reckhow, 1983).

Stream nutrient concentrations from non-point source runoff are functions of many parameters. For example, seasonal temperature variation, rainfall, and land use, land cover and management practice certainly affect nutrient concentrations and other constituents (e.g. dissolved oxygen). Spatial and temporal variations of land use, land cover and management practice can arguably be one of the main controlling factors.

In the study of 10 small coastal watersheds in South Carolina, United States, Tufford et al. (2003) pointed out that nutrient concentrations in forested streams were different from those in the urban streams, and nutrient concentrations varied seasonally. Multiple regression models to predict in-stream nutrient concentrations from land uses on small-scale watersheds suggested that effects were not significant (small r^2). This is because there may be a great deal of heterogeneity at the scale of very small watersheds, weakening the utility of analytical methods such as regression models because they assume some degree of homogeneity within categories. In other words, in order to reasonably and accurately predict in-stream nutrient concentrations one must introduce more than one parameter like land use into the model, if nutrient concentrations associated with small watershed are used.

In practice, however, a simple and yet feasible model is often sought. To develop a model that is technically defensible and sound, one has to often rely on a large amount of measurements and data analyses. In many circumstances, measurements are often limited or are hardly available and certain assumptions have to be made in order to make the best use of the available data. Keeping these factors in mind, a series of DRAINMOD (Skaggs, 1978) based models to predict nitrogen loading at the watershed outlet was developed for poorly drained coastal soils (Skaggs et al., 2003; Amatya et al., 2004; Fernandez et al., 2002). Models as simple as regression type (nutrient concentration as a function of flow and/or land use land cover) are also often used to estimate loadings.

For the ongoing CHS project, there were altogether 31 non-point source sampling stations in the watershed that have some water quality concentration measurements. Yet, at least 12 of them (EMPACT NPS sample stations, see Figure 3) were tidally influenced. To avoid any tidal flow interference, the water quality concentration measurements at these stations were not used in the data analysis and model development. The remaining 19 sample stations were used and their water quality data availability are summarized in Table 1.

Initial data analyses showed that the correlations between the median nutrient concentrations at 19 sample stations and the percentages of urban land use and percentages of forest that are associated with each sample station were relatively weak with small R^2. Because the sub-watersheds associated with stations JJG-NPS-1, JJG-NPS-2, JJG-NPS-4 were much smaller than the others they were excluded in the following data analyses. Furthermore, water quality concentrations were grouped into two categories: dry weather and wet weather. On the seasonal basis, however, the correlations between the median concentrations for dry weather or wet weather and percentages of urban land use and percentages of forest became relatively strong.

Based on these initial correlation analyses, multi-variable linear regression model was considered.

Table 1. Summary of NPS Stations and Nutrient Data Availability

Station ID	Nitrate(NO3)	NOx	NH4	TKN	Orth P	TP	BOD5	Fecal-Coli
Ashley _1	16/5	12/3	14/3	10/5	16/5	13/3	16/5	13/5
Ashley _2	20/7	15/5	18/5	20/7	20/7	17/5	20/7	19/7
Ashley _3	20/7	16/5	18/5	20/7	20/7	17/5	19/7	18/7
Ashley _4	20/7	16/5	18/5	20/7	20/7	16/5	19/7	19/7
Ashley _5	20/7	17/5	18/5	20/7	20/7	17/5	19/7	19/7
Ashley _6	20/7	16/5	18/5	20/7	20/7	17/5	19/7	19/7
Ashley _7	20/7	16/5	18/5	20/7	20/7	17/5	19/7	19/7
Ashley _8	20/7	16/5	18/5	20/7	20/7	17/5	19/7	18/7
Ashley _9	19/7	15/5	17/5	19/7	19/7	16/5	18/7	19/7
JJG-NPS-1	0/0	2/2	2/2	2/2	2/2	2/2	2/2	0/0
JJG-NPS-2	0/0	2/2	2/1	2/2	2/1	2/2	2/2	0/0
JJG-NPS-3	0/0	2/2	2/1	2/2	2/2	2/2	2/2	0/0
JJG-NPS-4	0/0	2/2	2/2	2/2	2/2	2/2	2/2	0/0
CSTL-013	0	0	101	99	0	133	160	157
CSTL-043	0	0	11	11	0	98	109	106
CSTL-063	0	0	234	232	0	222	244	247
CSTL-078	0	0	30	30	0	28	43	42
CSTL-099	0	0	109	110	0	144	165	151
CSTL-102	0	0	119	116	0	151	176	164

* Note: 16/5 means 16 measurements for wet weather and 5 measurements for dry weather.
for all CSTL stations, it was unknown if the measurements were taken under wet weather or not.

Multi-variable regressions can be utilized for forecasting purpose. The method examines how a number of variables has affected a dependent variable historically. From this, the relationship between these variables and the dependent variable can be expressed as:

Y = A+B1X1+B2X2+…+BnXn+E

Where:

Y = Predicted dependent variable value

A = the value of Y when all Xs are zero

X = the independent variables

B = the coefficients corresponding to the independent variables

n = the number of independent variables

E = an error term

By forecasting the independent variables, we can predict the dependent one. However, order to ascertain that the relationships are not coincidental, we must first assess the correlation between the dependent and individual independent variables. We can accomplish this by applying the Pearson Correlation Coefficient (otherwise known as ‘R’) to each independent variable. This tells us how much of the change in dependent variable can be explained by the change in independent one. Those variables with a high R^2 should then be used for multiple regression. The same correlation coefficient can be applied to multiple independent variables to ascertain how much of the change in dependent variable can be explained by changes in all independent variables.

In the model development herein, we chose percentage of urban land use and percentage of forest as two independent variables. The dependent variables will be nutrient concentrations, DO and fecal-coliform concentrations. Therefore, the regression equation will be, in general,

Y = a1X1+a2X2+a3

Where:

Y = nutrient concentrations, DO concentration and fecal-coliform

X1 = percentage of urban land use

X2 = percentage of forest

a1 = the coefficient corresponding to the independent variable X1

a2 = the coefficient corresponding to the independent variable X2

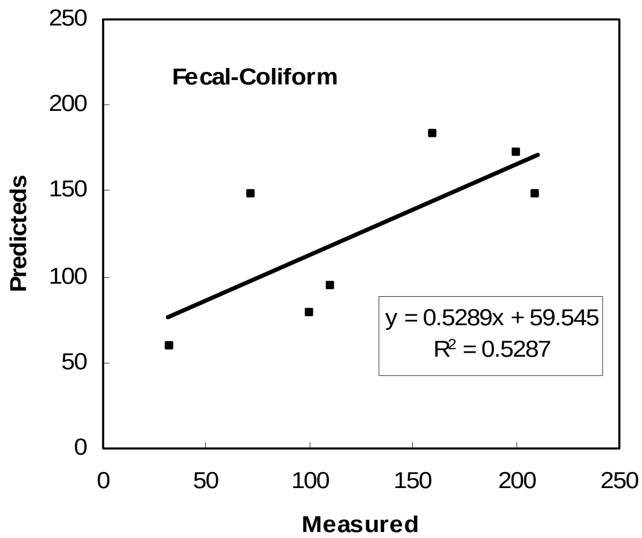
a3 = the value of Y when all Xs are zero

The multi-variable regression technique was applied to each nutrient constituent, DO and fecal-coliform. The resulting regression coefficients and R^2 are summarized in Table 2. R^2 was less than 0.5 for nutrients Nitrate/Nitrite and Ortho-P in both wet weather and dry weather conditions. For fecal-coliform in wet weather condition, R^2 was 0.45. As mentioned earlier, nutrient concentrations are not simply functions of land use. There are many other controlling factors that can alter stream nutrient concentrations.

Figure 4 shows two examples of measured versus predicted concentration using the multi-variable regression models presented in Table 2. Both models were able to predict fecal-coliform and BOD5 concentrations reasonably well.

Table 2. Summary of Multi-Variable Linear Regression Coefficients

Weather Condition	Nitrate(NO3)				Nitrate&Nitrite				NH4				
	a1	a2	a3	R^2	a1	a2	a3	R^2	a1	a2	a3	R^2	a1
Wet	-0.010	-0.010	0.730	0.530	-0.006	-0.009	0.631	0.490	-0.001	-0.001	0.126	0.633	-0.011
Dry	-0.009	-0.013	0.927	0.810	-0.007	-0.009	0.643	0.470	0.130	0.110	-7.090	0.650	0.080
Weather Condition	**Orth-P**				**TP**				**BOD5**				
	a1	a2	a3	R^2	a1	a2	a3	R^2	a1	a2	a3	R^2	a1
Wet	-0.010	-0.020	1.050	0.490	-0.006	-0.013	0.891	0.520	0.15	0.13	-4.28	0.69	14.65
Dry	0.002	-0.008	0.582	0.44	0.002	0.007	0.551	0.61	0.41	0.41	-21.7	0.81	12.37



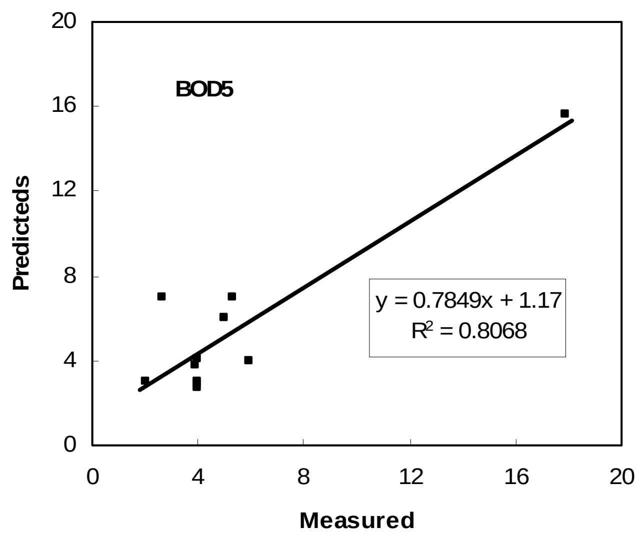


Figure 4. Measured versus predicted fecal-coliform (col/dL) and BOD5 (mg/L) concentrations for dry weather.

CONCLUSION

The models presented above were based on multi-variable regression and were used only for this watershed. One should not tend to generalize this approach unless site-specific data support such approach.

Data collected at reasonably large sub-watersheds should be used in multi-variable regression analysis because there is relatively less heterogeneity at large-scale watersheds than at small-scale watershed. Regression model will work relatively well for large watersheds because of some degree of homogeneity within categories.

To develop any statistical models, such as a multi-variable regression model, large amount of data are always necessary. Otherwise, the developed model may be misleading in prediction.

Even if the approach may be used in other watersheds, one should expect that all regression coefficients vary with different watersheds in different regions.

It should be pointed out that all the regression models developed here were based on nutrient data collected in upper Ashley watershed yet the models were applied to other sub-watersheds in the CHS watershed. Ideally, if nutrient data collected from other sub-watersheds were used in the model development the models would be more technically defensible.

For these coastal watersheds on poorly drained soils, given the availability of resources, data and parameters, DRAINMOD-based models can be used to reliably predict the flows and concentrations needed to estimate the nitrogen loadings from agricultural and forested lands.

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